APPENDIX

APPENDIX

Appendix includes photocopies of following documents.

1) Sanction letter Research and Development Grant from All India Council for Technical, Education (AICTE), New Delhi
2) Journal Publication

अखिल भारतीय तकनीकी शिक्षा परिषद्
ALL INDIA COUNCIL FOR TECHNICAL EDUCATION
(भारत सरकार का सांविधिक संस्थान) (A STATUTORY BODY OF THE GOVERNMENT OF INDIA)

24 MAY 1999

F.NO 8017/RDII/R&D/DLG (667)/98-99
March 27, 1999

THE PRINCIPAL
P V P VASANTRAODADA PATIL INSTITUTE OF TECHNOLOGY
BUDHGAON - 416304
MAHARASHTRA

Sub: Financial support under AICTE Programme of Research & Development (R&D) - approval cum sanction for the year 1998-99.

Sir/Madam,

With reference to your project proposal under the scheme of R&D for financial assistance, I am pleased to convey the approval of the Council for financial assistance as detailed here under:

1 Details of project for financial support,

a) Name of Chief Coordinator - S D LOKHANDE

b) Department – ELECTRONICS ENGINEERING

c) Project Title - ARTIFICIAL NEURAL NETWORK BASED IN LINE pH CONTROL ....

d) Approved Amount (in Rs.lakhs) - 4.02

e) Approved Duration of Project - 2 years (Two Years)

2. Further the Council hereby conveys the sanction for an amount of **Rs. 2.01lakhs** as First Installment of the approved grant for payment during 1998-99, in order to facilitate implementation of the project.

3 The First Installment would be released only on receipt of duly filled in TR-42 from the competent authority of the grantee Institutions. The sanction is valid for the financial year ending March 31, 1999.

4 The Chief Coordinator may immediately get approval from AICTE for the equipment and other items on non recurring head to be procured for implementation of the project by sending a priority list of equipment based on the discussion with the Experts, unless the list of approved equipment is not enclosed herewith.

P. V. P. I. T Budhgaon
Received on 5.5.99
Inward No. 136
Sent to

Cont 2

इंदिरा गांधी स्पोर्ट्स काम्प्लेक्स परिसर, इन्द्रप्रस्थ एस्टेट, नई दिल्ली - 110 002
Indira Gandhi Sports Complex I P Estate, New Delhi 110 002
Phone 3379010/11/12/13/15/16/17/18, Fax 011-3379002

5 The approved equipment should be procured as per the approved Govt. procedure only

6. The Second Installment of the grant will be released on receipt of the Progress Report as per Annexure - I and Provisional Utilisation Certificate of the First Installment as per Annexure - II as enclosed in the Terms and Conditions.

7. The Institution shall abide by all Terms & Conditions as enclosed herewith.

8. The expenditure under this grant is debitable to the AICTE head of Account 016/PLAN/ R&D.

It is requested that the TR-42 Forms duly filled may be submitted to Council at the earliest to facilitate release of grant during 1998-99.

Yours sincerely,

(Dr. R. Ramprabhu)

Copy to

1. LOKHANDE S D
   P A D VASANTRAODADA PATIL INSTITUTE OF TECHNOLOGY
   ELECTRONICS ENGINEERING
   BUDHGAON - 416304
   MAHARASHTRA

2. Accounts Officer, AICTE for release of grants.

3. Guard File

Encl: i) Terms & Conditions.
ii) TR-42.
iii) Approved list of equipments.

Internal Model Based Control of a Neutralisation Process: ANN Based Approach

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V.N. Bapat
Walchand College of Engineering, Sangli

Paper received : 19.10.02 Revised paper accepted : 6.9.03

In recent years, demand for best quality products is on the rise In respect of the process industry, this amounts to stringent automatic control systems. Moreover, plants tend to be more complex. There are two ways to deal with the non-linear control design for plants subject to uncertainty and disturbances: Robust control and Adaptive control. Recently neural adaptive control is being intensively developed. In the present work, a model-based control using ANN has been developed to control pH in a laboratory scale continuously stirred tank reactor (CSTR).

This paper demonstrates the extension of Internal Model Control (IMC) scheme to a neutralisation process. Firstly, the process as well as its inverse has been identified using back propagation algorithm for neural network training. Secondly, the IMC strategy has been used for neuro-control. The resulting controllers are comparable to gain scheduled PI or PID controllers, which are standard controllers in the process industry The performance of the neural net based IMC system is compared for the set point tracking with constant and non-constant disturbance rejection with conventional tuned PI controller. Experimental results using a laboratory setup test plant show the effectiveness of the proposed control scheme.

A chemical plant is a complex of many sub-unit processes and each sub-unit process may possess severe non-linearity due to inherent features such as reaction kinetics and transport phenomenon. Due to this complexity and non-linearity, conventional linear controllers, commonly used in industrial chemical plants, show very different control performances depending on operating conditions. In these circumstances, designing a robust controller using the assumption of linearity entails a degree of uncertainty in the design procedure. This, in turn, usually dictates that controller can operate efficiently within a limited operating region. The situation is further complicated by the fact that chemical process is often time variant and can contain significant time delays. The consequences of the combination of these factors usually mean that systems in the process industry cannot be efficiently operated under linear control, and hence, they are controlled in a conservative manner, never driven upto the system's achievable limits.

Many advanced control schemes are developed to efficiently control non-linear processes based on their mathematical models [1, 2, 3]. While the performance of these model-based strategies is influenced by several factors, it is principally dependent on the validity of the model. The development of such model-based control has relied on the linear systems theory. So the performance of the model based control strategies can deteriorate for systems which are poorly described by a linear model Thus, an accurate process model is a valuable simulation tool, which could be used to validate controllers to investigate the consequences of the proposed plant modifications or to recognise and subsequently prevent critical process operating conditions.

Control of a pH Process

The main difficulty of controlling pH processes in CSTR arises from the non-linear dependence of pH value on the amount of reagent. F.G. Shinskey [4] has shown that, if this non-linearity is severe and changes widely in an unpredictable manner, classical linear feedback does not always achieve satisfactory performance. One possible solution is to apply an adaptive controller, such as self tuning proportional-integral-derivative (PID) controller which is, in fact a minimum prediction error adaptive controller, based on an approximate linear process model

However, since the pH process is usually dominated by non-linear characteristics, it would be advantageous to use a non-linear model rather than an approximate linear model Grazyna A. Pajunen [5] simulated the non-linear adaptive controller based on combination of a pole placement design method with a piecewise-polynomial titration function, the coefficients of which are estimated from pH measurements. The results show that when titration curve is very non-linear in the operation range, then the non-linear adaptive controller works better than the linear one.

Model based control has the ability to handle constraints on actuated variables and internal variables. The most difficult part of the realization of a non-linear predictive control is to obtain a mathematical model. In many cases, it is even impossible to obtain a physically founded process model due to the complexity of the under lying processes. Bhat et al. [6] used neural computation for dynamic modeling and control of the non-linear processes.

Bhat and Mcavoy [6, 7] show the utility of the neural networks in providing viable process models where the technique is used to successfully characterize the non-linear chemical systems as well as to interpret the biosensor data. A. Drager [8] used a training set, which is generated by the system under closed loop control with a reasonable PI controller. The advantage of using the data

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from a controlled plant is that suitable time series of data can be extracted from normal operation data. Also collecting data from controlled plant goes beyond specific aspect that without control the plant can hardly be operated. In model-based control, a model of the process is an integral part of the control algorithm: the control equation structure depends on the process model in contrast to the PID controller, which has only one equation. It has been proposed by Narendra and Parthasarathy [9] and N.V. Bhat, P.A. Minderman Jr. and T J Avoy [10] that model based control strategies could employ neural network models and thus benefit from the non-linear approximation properties of ANNs. Also, efforts have been made to design a neural linearising control scheme for non-linear processes by Suk-Joon-Kim et al. [11] and by Psaltis et al. [12]. The present work is focused on studying the performance of the non-linear predictive pH control using neural model based on the IMC technique.

Internal Model Control with ANN Models

In model-based control, a model of a process is used to determine the control action. Garcia and Morari developed IMC structure for single input single output systems [13]. Also, this could include many conventional schemes such as Smith predictor, dead beat controller, Dalhin's method, etc. as its special cases. Garcia and Morari [14] extended the IMC controller concept defined for SISO system to multiple input multiple output (MIMO) system.

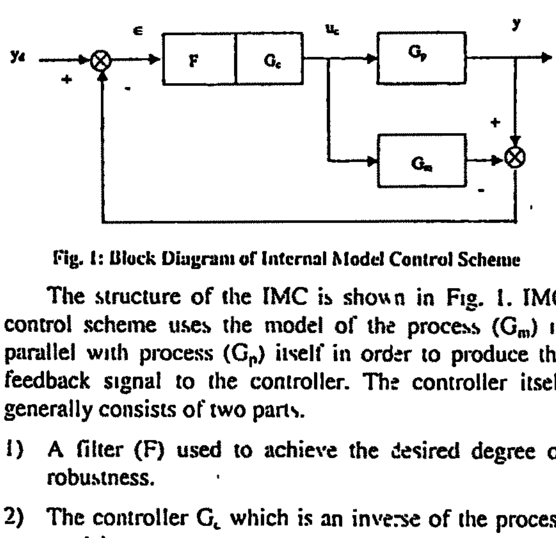

Fig. 1: Block Diagram of Internal Model Control Scheme

The structure of the IMC is shown in Fig. 1. IMC control scheme uses the model of the process (G_m) in parallel with process (G_p) itself in order to produce the feedback signal to the controller. The controller itself generally consists of two parts.

1) A filter (F) used to achieve the desired degree of robustness.
2) The controller G_c which is an inverse of the process model.

The internal model control loop uses the difference between the outputs of the process and of the internal model (G_m). This difference represents the effects of disturbances and of mismatch of the model.

Solving the closed loop response of this system yields :

$$y=G_p[I+G_c F(G_p-G_m)]^{-1}G_cFy_d=Ry_d \qquad (1)$$

where, R is the desired closed loop transfer function disregarding disturbances. This is typically a diagonal matrix of first order transfer functions. By simplifying the equation [1],

$$G_p[I+G_c F(G_p-G_m)]^{-1}G_cF=R$$

When solved for control plus filter G_cF yields

$$G_cF=G_p^{-1}R(I-R+G_mG_p^{-1}R)^{-1}$$

By approximating that model as equal to process, i.e., $G_m \equiv G_p$, the expression of control plus filter reduces to

$$G_cF=G_m^{-1}R$$

This transfer function, leads to the following properties.

1) Assume $G_c \equiv G_m^{-1}$

If the controller and the process are stable, then the closed loop stability is guaranteed.

2) The time constants of the filter should be chosen to give the desired response to set point changes and model/process mismatch.

In the general case, the error signal ε and the control action u are indicated by,

$$\varepsilon \;=y_d-(G_pu-G_mu)$$

$$u=G_cF\,\varepsilon$$

G_p u indicates the non-linear operator, G_p acting on the vector u. The above two equations yield:

$$u=G_cF[y_d-(G_pu-G_mu)]$$

Since $y=G_pu$ and $y_m=G_mu$, this equation can be written as,

$$Y=G_pG_cF[y_d-(y-Y_m)]$$

If the model is perfect, i.e., $G_p \equiv G_m$ and $y \equiv Y_m$, then the above equation leads to,

$$Y=G_mG_cF\,y_d=Ry_d$$

So, in order for the controller to track the desired reference trajectory, the controller can be the inverse of the model operator ($G_c \equiv G_m^{-1}$) and the filter can be equal the desired trajectory operator (F=R).

The equation for the controller becomes,

$$u=G_m^{-1}R\,\varepsilon=G_m^{-1}R[y_d-(y-y_m)] \qquad (2)$$

In order to incorporate the ANN model into this structure for the model process, Gm, then the controller, must be the inverse of this model. So the equation of the controller becomes.

$$u=\underbrace{G_m^{-1}}_{\text{ANN}}\cdot\underbrace{R}_{\text{Filter}}\underbrace{[y_d-(y-y_m)]}_{\text{Error signal}} \qquad (3)$$

In the implementation of the ANN IMC approach, the two neural networks substitute the nonlinear controller and the process model as shown in Fig (2).

The error signal is calculated by subtracting the difference between the forward model and the output, from the desired set point y_d. Then this error signal is passed through the linear filter, which has time constants that are related to the desired response of the system.

Finally, the inverse model needs to be obtained in order to calculate the filtered output. Developments of internal model control in case of the non-linear models of the process have been proposed by Hunt K. J., et al. [15, 16] for continuous time models and also for discrete time models.

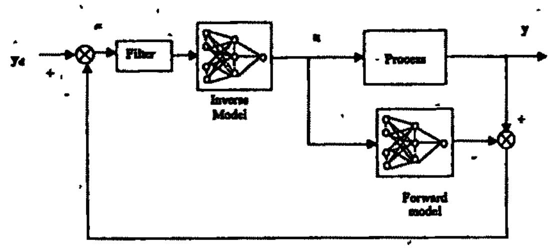

Fig. 2: ANN-IMC Approach

Illustrative Example

Continuously Stirred Tank Neutralization Reactor

A small-scale continuously stirred neutralization reactor is used in which acetic acid is neutralized with sodium hydroxide solution as shown in Fig. 3. The capacity of the tank is 6 lit. The concentrations of acetic acid and sodium hydroxide solutions are 0.01 mole/l. The flow rate of the acetic acid is maintained constant at 1.3 l/min, while the controller manipulates the flow rate of NaoH.

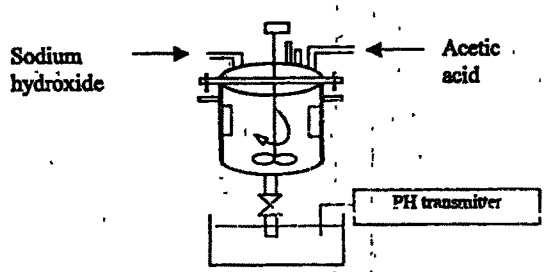

Fig. 3: Neutralization Reactor

McAvoy T.J., Hsu E. and Lowenthal S. [17] have developed a theoretical model of this weak acid strong base system. The chemical equilibria for the weak acid/strong base system are,

$$Na^+OH^- + CH_3COO^-H^+ \Leftrightarrow Na^+CH_3COO^- + H_2O \quad (4)$$

The pH can be obtained by,

$$pH = -\log [H^+] \quad (5)$$

The system will behave like a buffer solution due to the incomplete dissociation of acetic acid in water and the equilibrium reaction with sodium acetate. The CSTR is controlled using a digital PID controller The controller, in turn, is supervised by personal computer.

ANN Modelling of the pH Process

Internal model control structure as shown in Fig. 2 is used for the control. The IMC structure makes use of the process model to infer the effect of immeasurable disturbances on the process output and then counteracts that effect. The controller uses the forward and inverse of the process model.

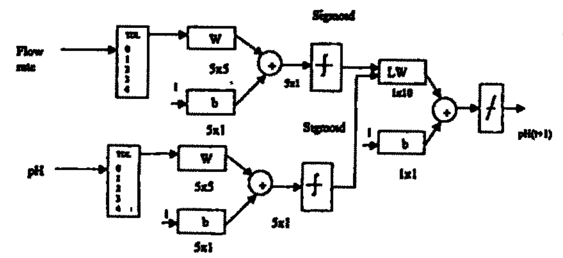

Fig. 4: Network Architecture

While developing a control scheme using the neural network as a process model, we need enough data to train neural network. Generally these data are obtained by making various random changes in process inputs over a whole operation range But this may lead to a very sparse representation of the high gain area at the point of equivalence in the training data set.

Various structures of the neural network have been tried. The neural network structure used in final control has three layers. All the layers are fully connected. Tapped delay line having five inputs is used at the input layer to obtain the delayed inputs during training. There are 10 neurons in input layer, 10 neurons in hidden layer and 1 neuron in the output layer. All the layers have the biases. Input and hidden layer use the sigmoid transfer function while the output layer uses the linear transfer function The network architecture is shown in Fig. 4.

Forward Model

Fig. 5 shows the steady state process characteristics of a pH process. The process has steep region where it has very high process gain. If random input is used for generating the data, it may lead to loss of response data in this region If the insufficient numbers of the data sets are available near the equivalence point, it might not properly model the steepest portion of the process characteristics.

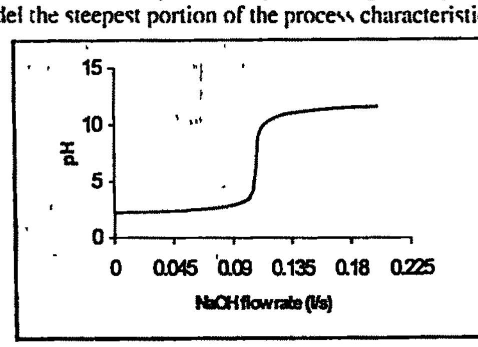

Fig. 5: Steady State Process Characteristics

The training dataset has been generated by the system under closed loop control with a PI controller. The sampling time is set at 20 sec. The set points are changed randomly during operation and the linear PID controller is allowed to track these set points. Thus, the training dataset consists of two measured time series of pH value and dosing pump frequency (output). The plant is operated for 3 hrs. The training data used to model the pH response is as shown in Fig 6.

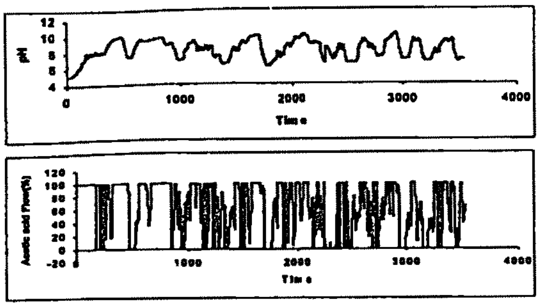

Fig. 6: Data Used during Training

A test data signal of about 1000 input-output pairs has been obtained in the same way. Various structure of the neural network has been tried. The multiple input single output (MISO) model finally used is,

PH(t+1)=N[pH(t), pH(t-1), pH(t-2), pH(t-3), pH(t-4) Flow(t), Flow (t-1), Flow (t-2), Flow (t-3), Flow (t-4)] (6)

Where N is neural network having 3 layers. All the layers are fully connected. Tapped delay line is used to obtain the past inputs. The architecture of the neural network is 10-10-1. All the layers have the biases. The input and hidden layer activation function are sigmoid in the range of (-1,1). Output layer has linear activation function.

Inputs to the neural network have been scaled in the range of (-1,1). The learning rate initially is $\beta = 0.94$ and momentum coefficient $\alpha = 0.4$. The mean square error (MSE) is less than 0.0001 on the tested results. Generally, training efforts are high, which makes it difficult and time consuming to explore various structures and to optimize the network structure. The stringency of the network structure chosen is not checked. Also it is observed that the number of neurons in the hidden layer has very little effect on the prediction. The actual and predicted model response have been compared and the prediction error found to be very small. This developed forward model has been used in the ANN-IMC controller scheme.

Inverse Model

The inverse model identification plays a central role in model based control structures as the quality of control depends directly on it. Neural network architecture, similar to the forward process model, can be used to obtain the inverse process model. The neural network model, used to learn the inverse dynamics, consists of delayed plant inputs and outputs.

The neural network model for the inverse dynamics of the process is a non-linear function, which consists of delayed pH output and input flow rates according to the estimated order and the dead time of the neutralization process. The inverse process model is developed by using the same training data. This network will predict the flow rate necessary to achieve the desired pH. A neural network architecture similar to the forward process model is used to obtain inverse process model.

Flow(t)=S[pH(t),pH(t-1),pH(t-2),pH(t-3),pH(t-4), Flow(t-1),Flow(t-2),Flow (t-3),Flow (t-4),Flow(t-5) (7)

Where, S is neural network similar to network used in obtaining the inverse model. The neural network is trained using both the main learning architectures for the inverse model, viz., 1) The general learning, and, 2) specialized learning. The inverse model trained using general learning often leads to situations in which the output of the controller sticks at some value, resulting in poor performance. In the present study, the specialized learning was used to obtain the inverse model

The model obtained has a good accuracy. Since most errors are due to the control saturation, adding neurons does not improve the training mean square error (TMSE) significantly and is around 1.5e-5. This obtained inverse model and the forward model are used in the IMC structure.

Experimental Results

The IMC systems are characterized by a control device consisting of the controller and the internal model of the process. The internal model loop computes the difference between the output of the process and the internal model. This difference represents the effect of disturbances due to mismatch of a model.

Comparison with the PI Controller

To check whether the neural network controller works well is to compare it directly with other types of existing controllers. As PID controllers are still the most widely used in industry, it is worthwhile comparing their performance. A velocity form of the discrete PID controller can be written as follows:

$$\Delta u(k)=K_c[e(k)-e(k-1)]+T/2T_i[e(k)-e(k-1] \quad T_d/T[e(k)-2e(k-1)+e(k-2)] \qquad (8)$$

where $\Delta u(k)$ is the increment of the control input, e(k) is the performance error at the sampling instant k, K_c is the controller gain, T_i is the integral or reset time, and T_d is the derivative or rate time. The auto tuning of the PID controller is done in which the process characteristics are measured and optimum values of the K_c, T_i and T_d are obtained. The final setting for Kc, Ti and T_d are 15, 5 sec, 2 sec respectively.

Setpoint Tracking

The experiments were performed using the neural network architecture as shown in Fig. 3. with the training data set values. The sampling time used for the PI controller and for the generation of the training data is 20 sec. The total number of the dataset points is 3600. After completion of the training, the prediction of the neural network has also been tested.

The IMC algorithm is implemented using the C. In order to obtain the better accuracy, the dosing pump is used to deliver the controller output to control the base flow. The training time required for both the networks is large. But once the trained network is used in the IMC control system, the controller output can be computed within the short time

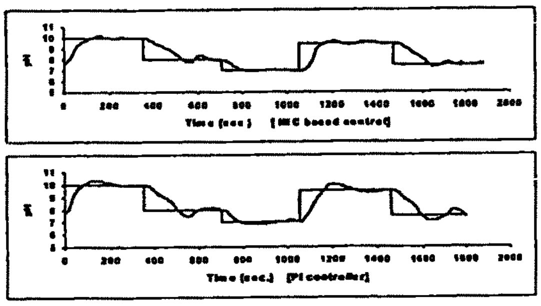

Fig. 7: Setpoint Tracking Performance

Setpoint tracking performance of the IMC based controller has been tested using the constant and non-constant disturbance. Fig. 7 shows that setpoint tracking performance of a typical ANN IMC is compared with PI conventional controller The experiment used consists of a constant disturbance flow and step changes are applied to the setpoint over the range of pH from 7 to 10. The controller regulating pH=7 has a regulatory performance measured as pH MSE (0.026) which is significantly worse than IMC based controller having pH MSE (0.0075). However, the IMC based controller performs significantly better than the fixed parameter PID controller when tested at different setpoints.

Disturbance Rejection

The disturbance rejection performance has also been tested as shown in Fig. 8. For providing a disturbance, a 30 per cent decrease of acid flow has been performed and this flow has been held constant afterwards. The IMC based controller regulating pH=8 has a regulatory performance measured as pH MSE (0.0065) which is significantly better than PID controller having the performance as pH MSE (0.048). The performance obtained with the neural network based IMC control system is very good.

Conclusion

The use of ANN to model and control a non-linear pH process has been investigated. A model based internal model control system is applied to the laboratory pH process. The neural network has computed the process dynamics in all the operation region of the process. The ANN IMC control system gives better results as compared with properly tuned PI controller in both set point tracking and disturbance rejection performance. The prediction of the pH one dead time ahead of in the future effectively removes the dead time from the control calculations. Modeling errors in the IMC system are always reflected in the disturbance estimate. Within the IMC system, such modeling errors are treated as disturbances in order to avoid offsets from the setpoint.

The main advantage of the IMC control system is that if the steady state gain of the controller is equal to the reciprocal steady state process gain of the process model, then there will be no offset for constant disturbance and constant setpoint.

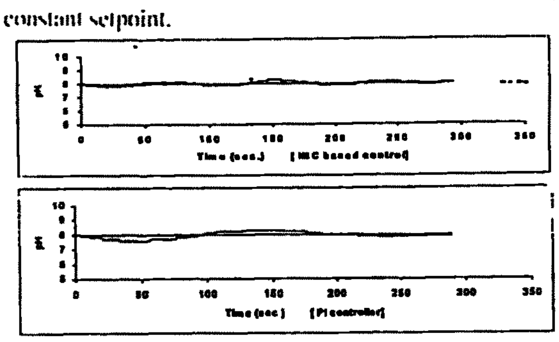

Fig. 8: Disturbance Rejection Performance

Acknowledgement

The authors thankfully acknowledge the financial help received from All India Council for Technical Education, New Delhi under the project No 8017/RDII/R&D/DEG(667)/98-99

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